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An Overview of a New Sensor Calibration Platform

P. Clausen [1], J. Skaloud [1], R. Molinari [2], J. Balamuta [3], W. Yang [3], J. Lee [3], S. Guerrier [3]

[1] Geodetic Engineering Laboratory, Ecole Polytechnique Fédérale de Lausanne, Switzerland
[2] Department of Statistics and Applied Probability, University of California, Santa Barbara, USA
[3] Department of Statistics, University of Illinois, Urbana-Champaign, USA

Goal: Stochastic Modeling of (Inertial) Sensors

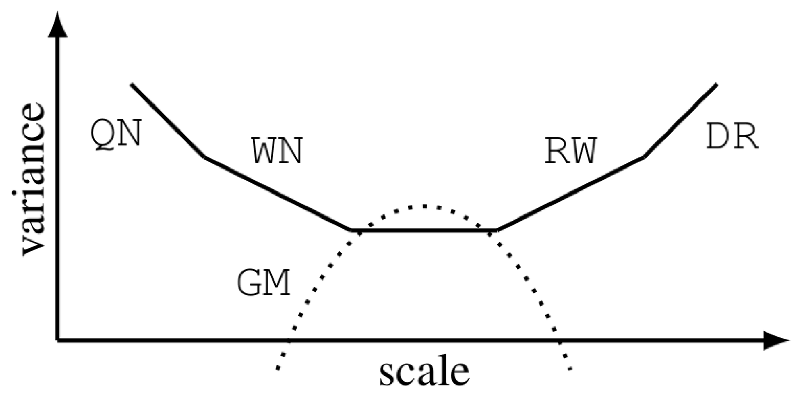
Inertial sensors have been employed in different types of applications in miniature embedded devices such as phones, watches, and small unmanned aerial vehicles. The **stochastic structure** of the error signal coming from these sensors is complex and needs to be determined for optimal fusion with other devices (e.g. GPS). The recently-proposed approach, **Generalized Method of Wavelet Moments (GMWM)** using the wavelet variance (WV), overcomes these limitations. The presented software platform can be used for stochastic calibration (i.e. parameter determination) of **IMUs or other types of sensors**. The software is **Open Source** and is developed within the broadly used statistical framework **R** using **C++** language.

What is behind GMWM?

GMWM finds a solution to the **minimization problem**, by looking for the proper parameters that match the 'empirical WV' and the 'model-implied WV'. Possible processes are: Quantization Noise (QN), White Noise (WN), Gauss Markov (GM), Random Walk (RW) and Drift (DR).

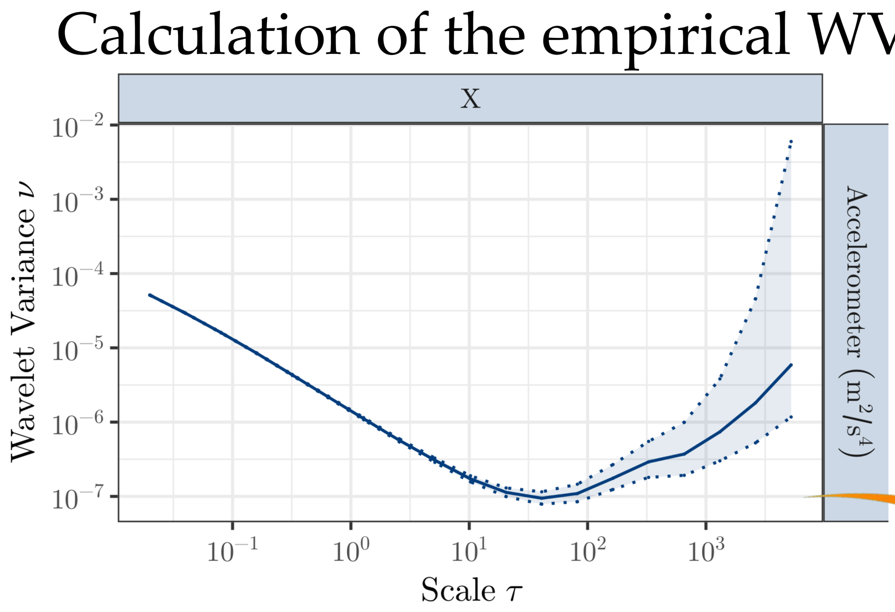
$$\hat{\theta} = \arg\min\left(\left(\hat{\nu} - \nu(\theta)\right)^T \; \Omega \; \left(\hat{\nu} - \nu(\theta)\right)\right)$$

θ: parameter vector
ν: model-implied WV
$\hat{\nu}$: empirical WV
Ω: weighting matrix

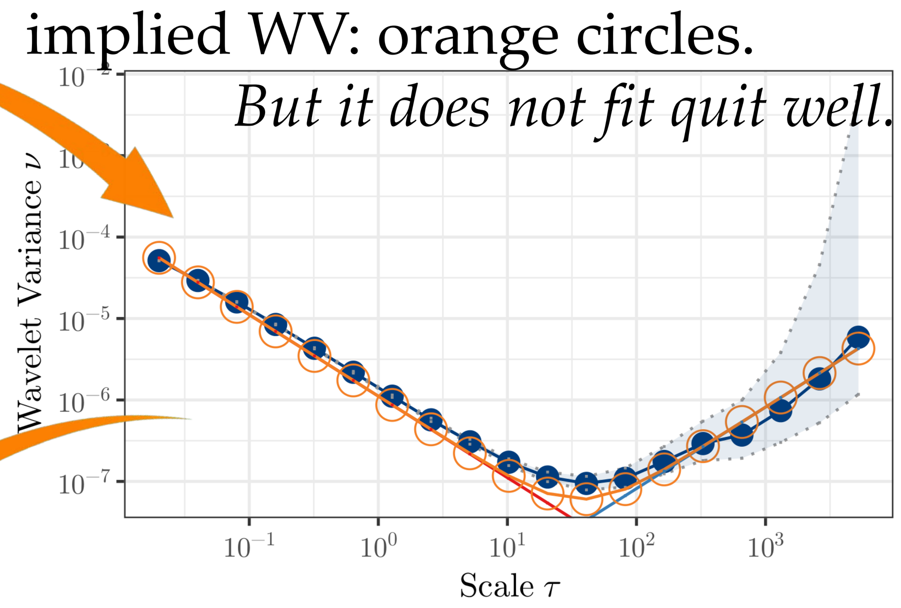


Calibration example

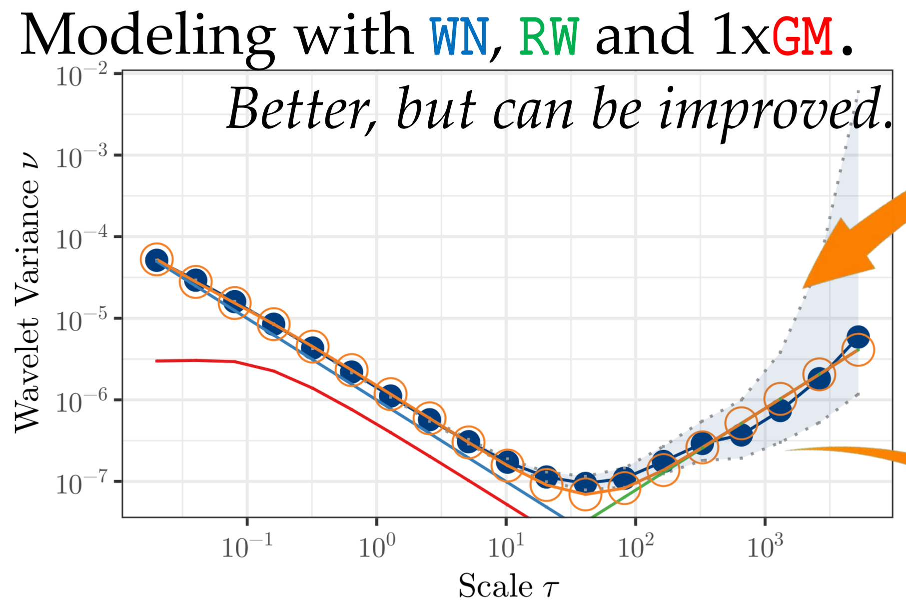
Calculation of the empirical WV from several hours of static IMU data.



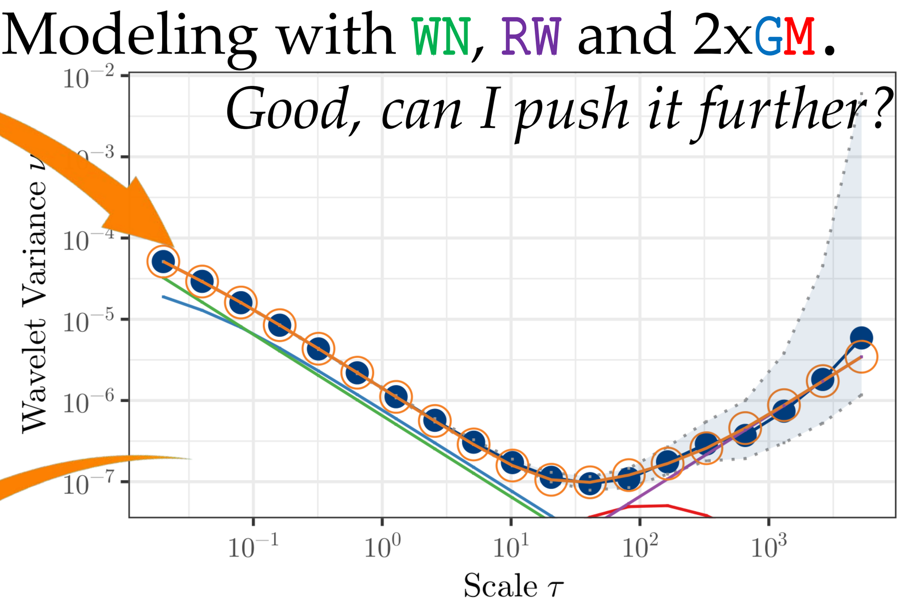
Modeling with WN and RW.
Empirical WV: blue dots. Model-implied WV: orange circles.



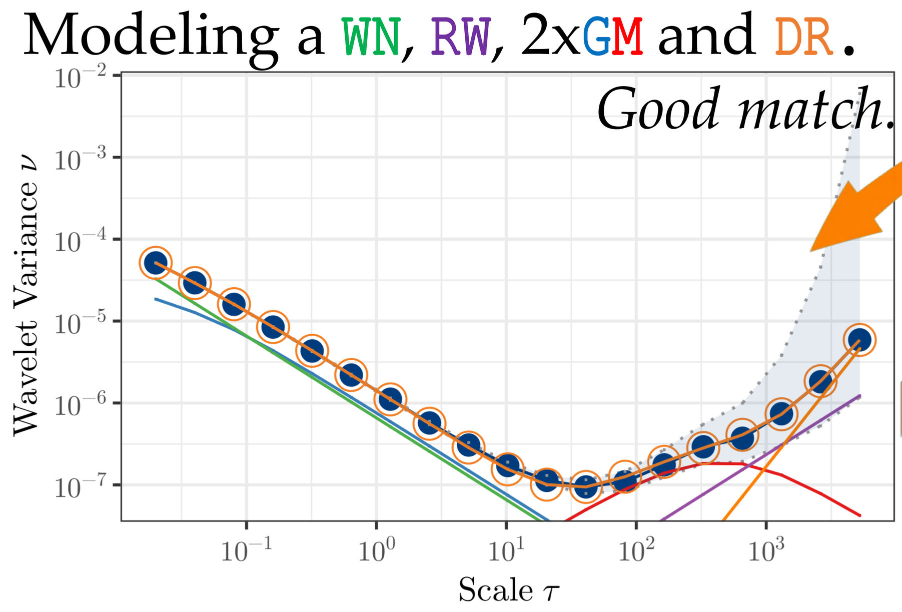
Modeling with WN, RW and 1xGM.



Modeling with WN, RW and 2xGM.



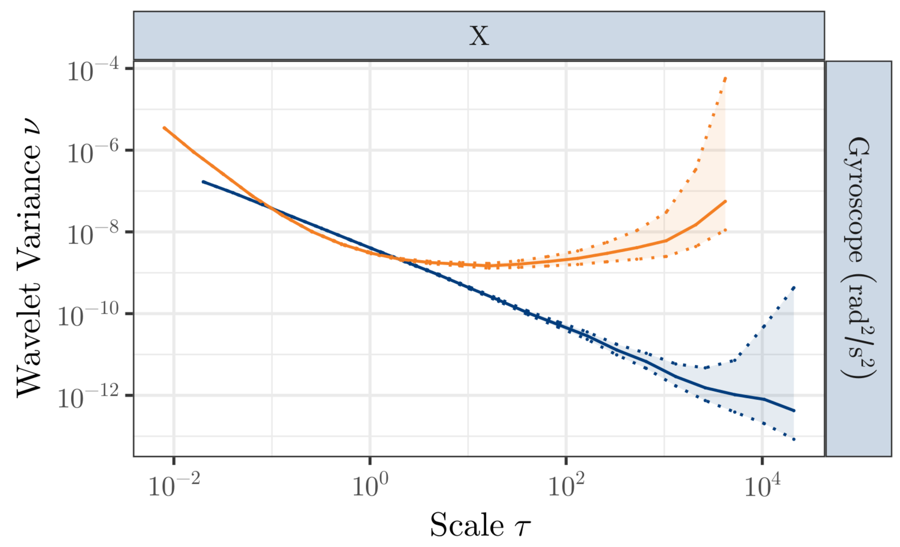
Modeling a WN, RW, 2xGM and DR.



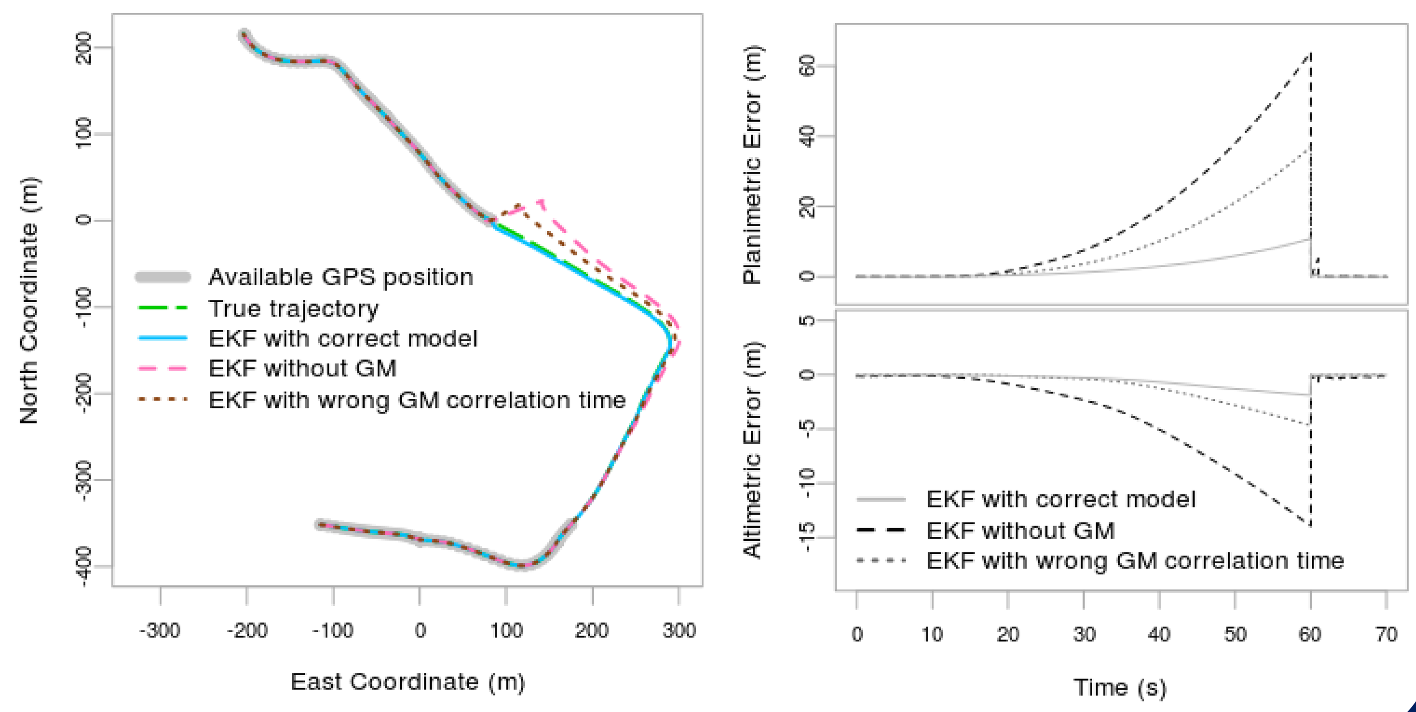
Parameter	Estimate	Lower CI	Higher CI
WN: var	6.566e-05	6.476e-05	6.657e-05
GM1: beta	1.477e+02	1.477e+02	1.477e+02
GM1: var	4.814e-05	4.727e-05	4.896e-05
GM2: ...	...	...	...

Application

Each sensor has its own noise characteristics. High grade IMUs (blue) have a precise and easy model, whereas low-cost IMUs (orange) show a more complicated error structure.



Precise knowledge of IMU sensor stochastics improves the navigation solution. The GMWM can provide these parameters.



Conclusion

- Statistically rigorous approach
- Models signals of complex spectral structure
- Computationally efficient algorithm
- Many types of different stochastic processes
- Manual or automatic model selection
- Increased navigation accuracy

References

1. S. Guerrier, J. Skaloud, Y. Stebler, and M. P. Victoria-Feser, "Wavelet-Variance-Based Estimation for Composite Stochastic Processes," Journal of the American Statistical Association, vol. 108, no. 503, pp. 1021–1030, 2013.
2. J. Balamuta, S. Guerrier, R. Molinari, and W. Yang, "A Computationally Efficient Framework for Automatic Inertial Sensor Calibration," Submitted manuscript, Full text: https://arxiv.org/abs/1603.05297, 2016.
3. S. Guerrier, R. Molinari, and Y. Stebler, "Theoretical limitations of allan variance-based regression for time series model estimation," IEEE Signal Processing Letters, vol. 23, no. 5, pp. 597–601, 2016.
4. S. Guerrier, R. Molinari, and J. Skaloud, "Automatic Identification and Calibration of Stochastic Parameters in Inertial Sensors," Navigation, vol. 62, no. 4, pp. 265–272, 2015.